The Economic and Environmental Effects of Seasonality of Tourism: a look at Solid Waste

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October 16, 2020

Abstract

Tourism is traditionally associated with great opportunities of growth with relatively small investments in physical and human capital, but also with high levels of negative externalizes, particularly referred to the environment. Sometimes those externalizes are easy to be quantified even though are difficult to be internalized because of poor management schemes. This paper aims at giving some evidence of the environmental cost of tourism in terms of solid waste produced in municipalities in Tuscany. There is very little literature that addresses the relationship between the production and cost of solid waste and tourist presences, and none, that I am aware of, that look at the seasonality of tourism. I borrow from the literature on Data Envelopment Analysis (DEA) to estimate the efficiency of Decision Management Units (DMU) where the units are represented by municipalities, and I then relate the measure of relative efficiency to spatial and tourism related variables. I also look at the scale of the DMUs to see if the seasonality of tourism has a particular impact on the ability to operate at the optimal scale. The empirical analysis suggests that (1) seasonality has a negative effect on the efficiency of solid waste management, (2) that this effect is primarily due to the difficulty to operate at optimal scale and (3) that it is especially the seasonality of arrivals that negatively impacts efficiency while the average stay at pick season has an opposed positive effect. The implications of these results are that more effort has to be made in managing flexibly solid waste collection in those localities affected mostly by seasonal tourism, or spread more evenly tourism over the year and incentivate longer stay rather than higher number of visitors. Alternatively, or as a policy instrument for these objectives, a flexible tourist taxation as a function of touristic presences and length of stay could be introduced.

Keywords: Sustainable tourism; Seasonality; Quantitative research; Indicators; Environmental impact assessments.

JEL codes: Q51; Q53; L83

1 Introduction

Tourism, unlike many traditional service sectors of the economy, is one that relies heavily on public goods and/or produces a great deal of externalizes. In this paper I look at the effect that tourists might have on the efficiency of solid waste management in Tuscan municipalities. I look in detail at some characteristics of tourism that might exacerbate the effect due to increased presences. That is, I look at the uneven distribution of presences across seasons (seasonality of tourism), and how this might impact the ability of municipalities to manage the collection and recycling of solid waste. Seasonality in tourism is seen as a problematic feature for businesses, but also for the communities of those locations that are most affected by it. Businesses, such as hotels, restaurants etc... are unable to take full advantage of their investments for most of the year when presences are low, while communities might live the negative effects of a highly concentrated flow of tourists for a short period of time of the year, such as congestion on traffic, water supply, waste management etc... Seasonality of tourism also requires an extra effort of local administrations that need to provide for services such as policing, traffic control, water management and solid waste management among other things. The purpose of this paper is to look at this last possible effect of tourism seasonality, how it may affect the efficiency in waste collection and recycling. This is an important question in that often decisions about waste management are made following "best practices" that are not always and generally applicable to all municipalities in the same way as they might be affected by different exogenous phenomena such as seasonal tourism. For localities were this phenomenon is present and important, more flexible organizational rules might improve efficiency, for example scaling up and down the size of the organization for what can be done (labor, collection facilities etc...). The effect of tourism on the efficiency of waste management has been the object of other studies. Among many that report case studies of small localities, often islands, one close to my work is the study conducted by Mateu-Sbert, Ricci-Cabello, Villalonga-Olives and Cabeza-Irigoyen (2013) which focuses on the impact on waste production that touristic presences have as compared to residents. The paper reports an interesting quantification of this impact from which it is also possible to derive the importance of the seasonality aspect, even though not directly measured per se. The study is limited to the Spanish island of Menorca, but suggestive of a phenomenon that can be more general. The findings are that touristic presences significantly impact the production of solid waste, however less than residential presences, in contrast, tourists recycle less than residents (residents recycle 47.3% more than tourists). The latter gives an important indication of possible efficiency problems related to touristic presences. The study however does not address the issue of efficiency of solid waste management, but only its production, therefore does not address the issue of seasonality on efficiency that can come as an additional effect of touristic presences unevenly spread of the year, due to difficulties to adjust the management of collection. Greco, Cenciarelli and Allegrini (2018) also analyze the effect of tourism on solid waste management, this time on the unit cost per kilogram. They look at several variables related to tourism and also decompose the collection of solid waste in different recycling and non recycling activities and they find a significant impact of tourism in increasing the cost of waste management per unit of waste collected. Their work is the first and only work that look closely at the relationship between tourism activities and such an important indicator related to the efficiency of management of environmental resources. Their work, however, pose more questions that the ones they answer, and in particular why is it that tourism has so much of a negative impact on waste management efficiency? This is a very important question as it also relates to the possible negative effects that tourism might have on local communities that may need to pay the price of these inefficiencies. Another strand of the literature that focuses on the efficiency of solid waste management exists, and it is based on data envelopment analysis.

Data Envelopment Analysis (DEA) is a powerful benchmarking tool that associates the values of arrays of inputs to arrays of outputs, and calculates how different decision units compare to one another in terms of the possibility to change the composition of inputs (outputs), to obtain the same outputs (inputs). In other words, identifies the most efficient decision units among many and scores the other in terms of how far they are from that efficiency. Efficiency is, however, always defined in terms of inputs or outputs and can never be an absolute measure. DEA is a non-parametric approach, that is completely agnostic about the functional form of the production system. It is also possible to calculate the efficiency imposing the same scale to all units under investigation, or letting the units free to operate at different scales, those different measures give the idea of how far one unit can be from its optimal scale and how much that costs in terms of efficiency. In this sense, in the literature on DEA benchmarking, another index called Scale Efficiency Ratio (SER) is used, computed as the ratio between the score of the overall efficiency of the DMU j and the score of the efficiency at the given scale of production of the same unit. The SER index isolate the scale effect of possible inefficiencies that in administrative divisions can be quite significant.[1]

The idea of applying the Data Envelopment Analysis (DEA) to look at the efficiency of different Solid Waste Management Units, also called Municipal Waste Management Systems (MWMS) with Italian data was first proposed by Sarra et al. (2017). Using data from ISPRA, the same data I use in

[1]An thorough explanation of the DEA method that I am using here with an exhaustive review of the literature is provided by Sarra, Mazzocchitti and Rapposelli (2017). I also follow their work in much of the analysis and use the same data-sets for part of the results. I remind therefore the reader to their work for more details.

this paper, they calculate scores for the municipalities of Abruzzo in Italy, calculate the efficiency scores and the Scale Efficiency Ratios (SERs) of those municipalities and relate those scores to exogenous variables to look into what could affect inefficiencies and in particular scale inefficiencies in waste management in Italy. Among their variables geographical indicators such as altitude, population and income per capita are used together tourism measured as the number of tourist per person in a given year. In this paper I propose a possible explanation that is in line with textbook economic theory. Tourism, as well as other activities that are related to the exploitation of the "good season", can be a highly cyclical business and such seasonality may well interfere with the predisposition of the proper scale of operation at any point in time as needed. Inefficiencies can therefore arise because of inappropriate seasonal scale, being too small in high season and too large in low season. In this paper I follow the work of Sarra et al. (2017) closely, with some exceptions: first of all I use more detailed data on tourism and in particular I use indexes of seasonality of tourism; second, I use data on municipalities in Tuscany, that is because I have available detailed data on tourism and also Tuscany is one of the most visited regions in Italy and tourists are not concentrated only in few cities; third I follow a more traditional approach looking at correlations by means of OLS regressions, however to run OLS I transform the dependent variable with a -log transformation so that its domain goes from zero to plus infinity.[2]

2 Data

I use data on municipalities of Italy from different sources. For waste management I use data from ISPRA[3], which provides very detailed data on quantities and costs of waste collection by municipalities for about the whole Italian territory. It also provides details on how much waste is collected as recyclable. From Istat I collect information about the municipalities such as if they are coastal locations, or other tourist traits. All data from ISPRA and Istat are annual and available for the latest years up to 2018. Finally from the data base of tourism of the Region of Tuscany I collect data on arrival and presences of tourists by quarter, information that I use to assess the seasonality of the touristic flows, this dataset also gives data on municipalities from 2005 to 2019, I therefore take an average of the cycles of all these years. For ISPRA data I take the latest year which is 2018, however not all municipalities are present all years so that I augment the observations looking at the

[2]The literature proposes a Tobit approach, however Tobit models are valid for dependent variables that present a truncation and, as such, have a mass around the value of the truncation. The efficiency score is not truncated but simply built in such a way that limits its values between zero and one, and unlikely presents masses at the boundary values. For this reason I prefer a transformation that allows the dependent variable to be in the same domain of the dependent ones.

[3]Istituto Superiore per la Protezione e la Ricerca Ambientale.

year 2017 as well, still some are absent and are not included in the analysis. I do not take earlier years as efforts in improving recycling and therefore efficiency in collecting solid waste is ongoing, so that comparing different municipalities at different points in time does not give a good picture of geographical differences, which is the source of variation I exploit for looking at the effect of tourism seasonality. Moreover, as I look at an index of seasonality that is built using quarterly time series of flows of tourists, I do not exploit the panel nature of the ISPRA data, rather I look at the latest year of data available assuming that this year represents the best effort of making the collecting process as efficient as possible. Table 1 gives a summary of the data, with mean values and variation of the variables.

Table 1: Summary of Variables

Summary of Waste Variables		
Variabile	Mean	St. Dev.
Total Differentiated Solid Waste (tons)	4227.6848	6532.8977
Total Undifferentiated Solid Waste (tons)	7816.7726	12202.1505
Total Cost per Kg of Solid Waste	38.7796	10.6165
Percentage of Differentiated over total	0.5165	0.2072
Summary of Tourism Variables		
Total Presences	145189.4057	288028.0792
Pick of Presences	2.0416	0.4776
Ratio on Pop. of Presences	22.6335	57.8825
Intensity of Presences	62285.1534	142137.9636
Total Arrivals	41559.4245	91442.8900
Pick of Arrivals	1.7548	0.3841
Ratio on Pop. of Arrivals	Inf	NaN
Intensity of Arrivals	11049.3863	22520.2563
Other Variables		
Population	13007.8349	19217.6103
Area (kmsq)	86.5698	66.6353
Altitude (m)	264.8443	218.0140
Costal (dummy)	0.1462	0.3542

Cost figures are calculated in euros and refer to the cost on one kilogram of solid waste collected, while the amounts are in tons. The indexes are calculated as follows,

$$\begin{aligned}
\frac{1}{T}\sum_i pick(x_{ij}) &= \frac{4}{T}\sum_i \frac{\max_q x_{ij}}{\sum_q x_{ij}} \\
\frac{1}{T}\sum_i ratio(x_{ij}) &= \frac{1}{T}\sum_i (\frac{\max_q x_{ij}}{\min_q x_{ij}})
\end{aligned}$$

$$\frac{1}{T}\sum_i int(x_{ij}) \quad = \quad \frac{1}{T}\sum_i(\max_q x_{ij} - \min_q x_{ij})$$

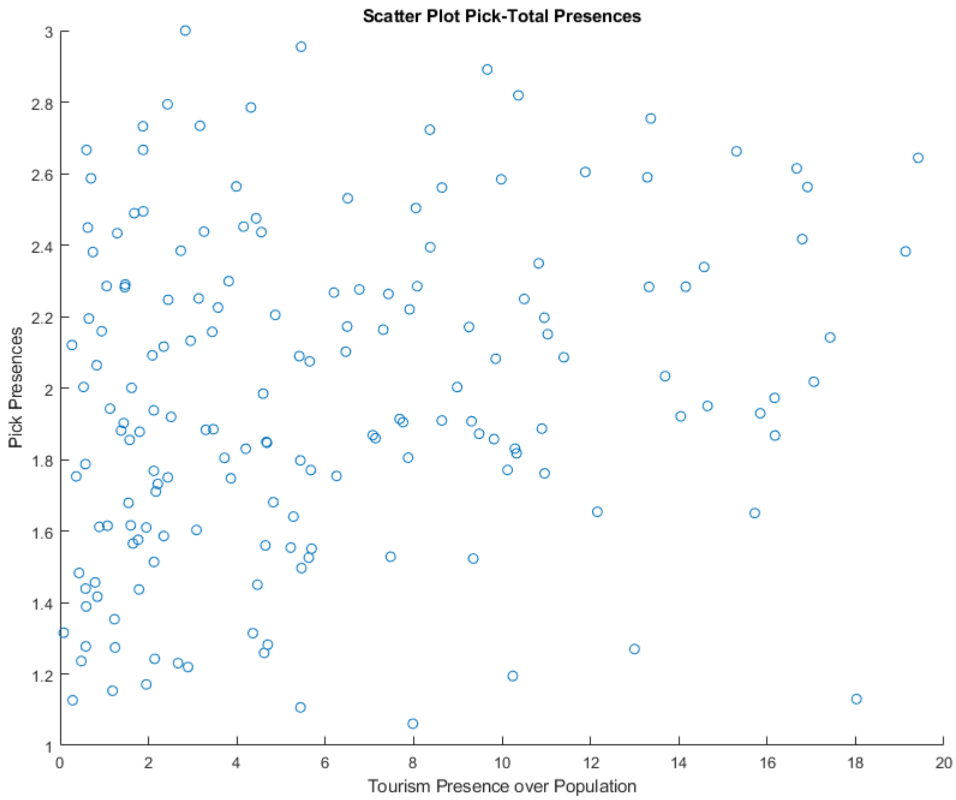
where the subscripts q, i, j stand for quarter, year and municipality. So that the pick is an average across years of the highest flow of tourists divided by the average flow of the year, the ratio if an average of the ratio between the highest and lowest flow within each year, and the intensity if the difference of the highest and lowest flow within each year. Each index is reported for both arrivals and presences, where arrivals are the head-counts of tourists arriving in a municipality, while presences is the product of arrivals with the nights spent by each tourist.

As the Table suggests in all variables there is considerable variation. Pick presences for example, one of the most looked up variables in tourist management studies, reveal an average of about 2 with a standard deviation of about 0.5, which means that there are municipalities where tourism is quite spread over the year (1 would represent an a-cyclical presence), and others where the highest season collects most of the tourists (4 would tell all tourists stay in one season only). Other two indicators of interest also show quite a significant variation, the cost of collecting solid waste, with a 40 euros average and a 10 euros standard deviation and the percentage of differentiated waste collection, with an interesting 50% average and 20% standard deviation. In the next section I go deeper in the analysis of these data looking at some interesting correlations among those variables in a visual way, with scatter plots, then I present the results of the DEA analysis and in conclusion I relate those results with tourism variables.

3 Empirical Evidence

First of all, as we know from the previous study of Greco et al. (2018), even though with slightly different data, tourism has an important effect of the efficiency of waste collection. In order to disentangle the effect of the seasonality of tourism from tourism presences per se, we need to be sure that the two variables are not too correlated, that would be the case if tourism if always seasonal everywhere. Fortunately, particularly in Tuscany there are various types of tourism, usually classified into three main types: Art-City Tourism, Florence, Siena, Arezzo but also many smaller municipality enjoy this type of tourism; Thermal (spa) Tourism and Coastal Tourism. Each type my have some degree of seasonality, but without any doubt the first type presents the lowest seasonality, as art cities are always available, while also spa tourism present a slightly higher but still reduced seasonality. Coastal tourism is the type that, for obvious reasons, presents the highest degree of seasonality. The following Figure 1, shows the relationship between pick of presences and overall presences as ratio of population, indeed we cannot spot any particular patter from the scatter plot, which tells us that the two variables are likely uncorrelated and therefore we can be confident on the possibility to identify a specific effect of the seasonality of tourism independent on the overall tourism effect.

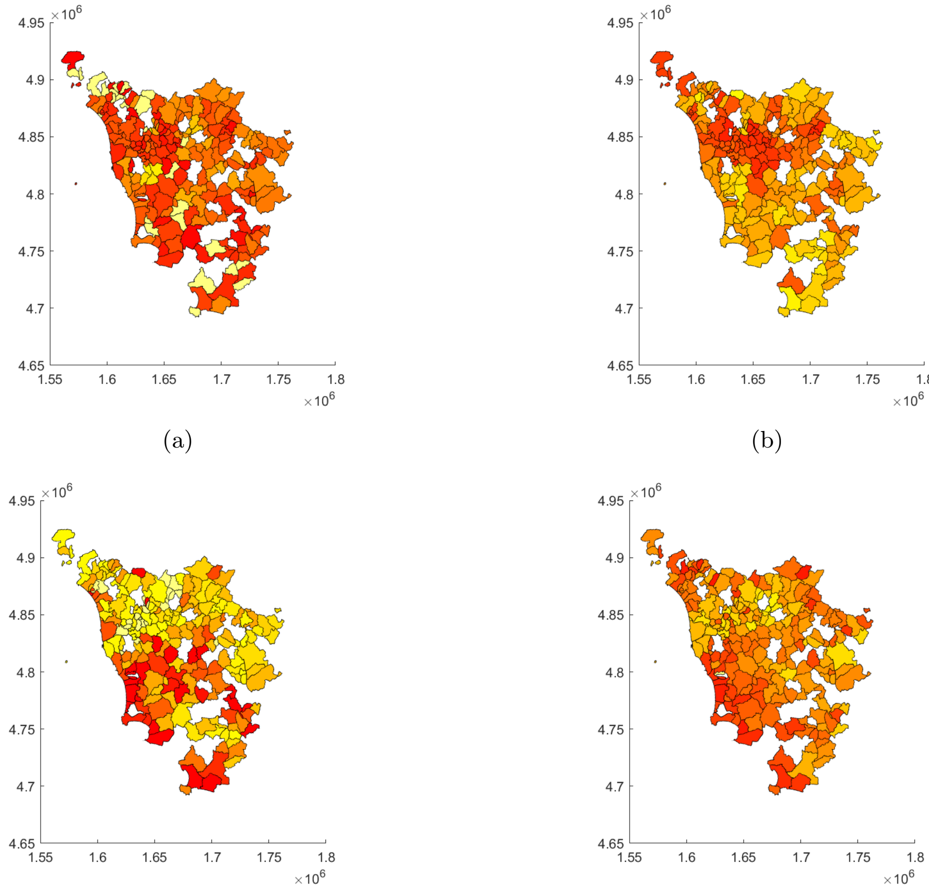
Figure 1: Relationship between Presences and Pick Presences



In Figure 2 I present a second group of graphs showing the region of Tuscany divided in municipalities for which I associate colors from yellow to red indicating low to high values of several variables. In panel A the cost per kilogram of solid waste collected, in panel B the share of recycling done, in panel C the overall presence of tourists divided by the population and in panel D the pick in presences.

As we are interested in the efficiency of solid waste collection, we consider recycling as a good outcome or output while undifferentiated waste as a bad outcome, and the overall cost of operation as a summary value of inputs. Panel A and B tell us something about efficiency in that show cost per kilogram and percentage of recycling. From Panel A we see that the cost per kilogram is a bit scattered around the Region, but higher costs are consistently present in the Val D'Arno area (roughly around $(1.65,4.85)*10^6$), which is a highly industrialized area compared to the rest of Tuscany, and in coastal areas compared to mountainous internal areas. The white areas are municipalities for which we don't have complete data. Looking at Panel B we see that the Val D'Arno area is also quite

Figure 2: Tuscany



(a) (b) (c) (d)

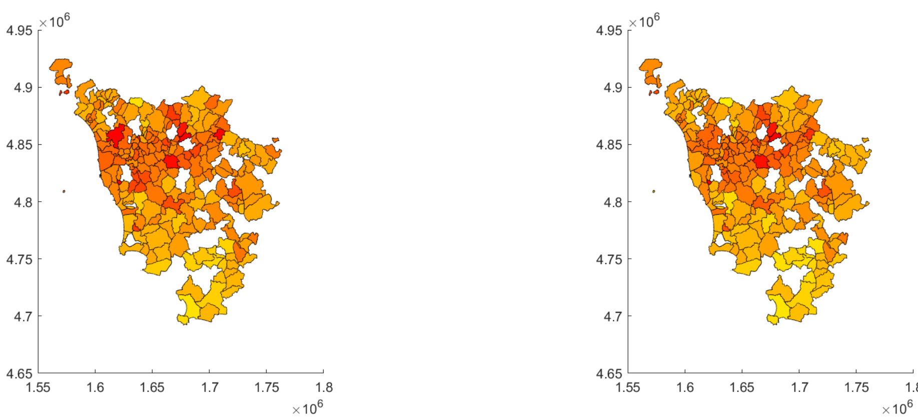
strong in recycling, while costal areas are much weaker and particularly so the southern areas of Tuscany also known as Maremma. Panels C and D tell us about tourist presences. Panel C gives a measure of tourism compared to the resident population, we can see here that the most affected area in terms of this indicator are the coastal and southern areas. Locations such as Pisa and Livorno as well as Florence do not appear particularly "hot" here because of the much larger population compared to southern municipalities. Finally, Panel D gives an idea of seasonality as measured by the pick in presences across the year. Again the Southern areas present a much higher seasonality that others, even those that do not have high rates of presences overall as the more internal areas of the Maremma region. To put together the first two panels into a measure of efficiency in the next subsection I present the DEA analysis that uses solid waste collection data in a linear programming type of algorithm benchmarking municipalities from most to least efficient. Those benchmark scores will then be used to analyze the impact of tourism on the efficiency of this sector.

3.1 Data Envelop Analysis

In this section I present the results of the Data Envelop Analysis (DEA) for the same municipalities of Tuscany. To evaluate the efficiency of the Decision Management Units (DMUs) I follow Sarra et al. (2017) and use the models introduced by Charnes, Cooper and Rhodes (1978) and Banker, Charnes and Cooper (1984) for computing constant returns to scale (CRS) and variable returns to scale (VRS) efficiency scores. Given that waste management has desirable and undesirable outputs, as in Sarra et alii I include undesirable among the inputs in a input-oriented efficiency evaluation. For computations I use the Matlab toolbox developed by Alvarez, Barbero and Zofio (2016).[4]

I therefore use as input the total expenditure on solid waste collection measured in euros, as a desirable output the total of recycling solid waste produced and as undesirable the total of undifferentiated solid waste both totals in tons. Figure 3 shows the scores for each municipality in a geographic map, the scores are from 0 to 1 and from yellow to red, therefore red municipalities are the most efficient. Panel A reports CRS score while panel B VRS. Figure 4 reports the ration of CRS/VRS, that is the Scale Effects (SE).

Figure 3: Data Envelopment Analysis - CRS and VRS



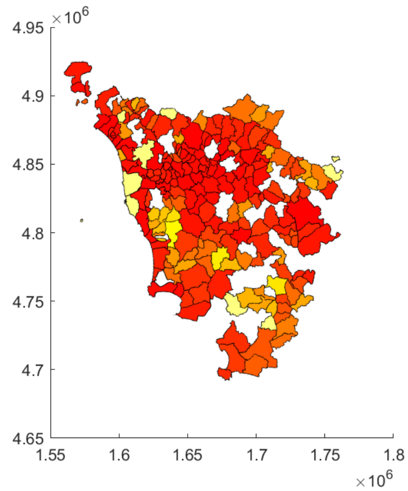
(a) (b)

Not surprisingly, having seen the evidence presented above, the lowest scores in terms of efficiency appear in the Southern part of the Region, the Maremma area in particular and also in the coastal areas. This is true for both CRS and VRS scores. What is not evident from Figure 3 is the relationship between CRS and VRS scores, which is also of interest to understand if inefficiencies are due to scale effects. To see this we can look at Figure 4 where we can clearly notice that the Southern and coastal areas of the Region also perform worse in terms of Scale Efficiency (SER), while especially the area

[4]They also provide an algorithm to take into account undesirable outputs directly, I use this algorithm too obtaining scores that are highly correlated (¿0.9) with the score I obtain by simply including undesirable outputs as inputs.

of Val D'Arno seems to operate at optimal scale, at least compared to other areas of Tuscany.

Figure 4: Data Envelopment Analysis - Scale Effects



Next step is to see if tourism plays a role in explaining those differences. Tourism is a very large sector in Tuscany, in 2018 the number of presences were more than 47 millions, which places Tuscany third in Italy after Veneto and Trentino-Alto Adige with more than one fifth of the whole tourist presences in the country. However, while Florence is certainly the main attraction within the region, differently from Veneto and Lazio with Venice and Rome respectively, Tuscany enjoys a touristic presence much more spread over the region as it also has some of the most popular coastal and thermal resorts that attract tourists from Italy and from abroad. It is therefore extremely important to analyze the impact of tourism and the way it manifests itself on environmental resources.

3.2 Factors Affecting Efficiency

In order to look at exogenous factors that may affect the efficiency of solid waste management I resort to regression models and to spatial models to account for possible spatial autocovariances. There are several reasons to think that observations are spatially correlated, first of all because being the observations geographical entities they may present some degree of interdependence due to proximity that may correlate with the variables we study. Even more important, although municipalities are the management units for solid waste collection, they most often resort to services that are supplied by one or few entities covering an area of more municipalities. In this sense, the efficiency measures may be correlate spatially because of the common provider. Other issues may arise from competitive behavior, imitation etc... The two models I use are therefore the simple OLS model, as a benchmark,

$$Y = X\beta + \epsilon \tag{1}$$

where Y is one of the three indices that proxy for efficiency and X is the matrix collecting the explanatory variables, and the Spatial Autoregressive (SAR) model[5], which is able to capture and distinguish the possible direct and indirect effects of the exogenous variables on the endogenous one taking into account the feedback due to the spatial autocovariance.

$$Y = \rho W X + X\gamma + \eta \tag{2}$$

where W is a weighing matrix that in this particular case is given by the distance of the municipalities in terms of kilometers of road between them. The data is provided by ISTAT.

3.3 OLS and SAR Results

The variables I use for the first set of results are the pick in presences, which is the variable of interest, the size of residential population, the share of presences with respect to population, altitude and a dummy for coastal areas. Tables 1 and 2 report the first round of results from OLS regressions.

In Table 1 the efficiency scores considering constant returns, variable returns and the scale efficiency score are regressed on a set of control variables, population, presences per resident, coastal area and altitude, that all can affect the efficiency of waste management and could also be correlated with our variable of interest which is the seasonality measure of tourism captured by the pick of presences. In particular presences per resident, coastal area and altitude are certainly correlated with seasonality and in principle could also be autonomously affecting the efficiency of waste management. For example for altitude because in mountainous regions could be more costly garbage collection given the morphology

[5]See LeSage (2008) for all the details of the SAR model.

Table 2: OLS I

Dependent Variables:	CRS-Efficiency Scores (a)	VRS-Efficiency Scores (b)	SER-Efficiency Scores (c)
Intercept	-0.23215	-0.41609	1.12285
	(0.15429)	(0.14434)	(0.05749)
Pick Presences	-0.10144	-0.01743	-0.06959
	(0.07565)	(0.07078)	(0.02819)
Population	-0.00034	-0.00001	-0.00049
	(0.00181)	(0.00170)	(0.00068)
Presences per Resident	-0.00119	-0.00172	0.00033
	(0.00096)	(0.00090)	(0.00036)
Coastal Area	-0.42012	-0.30223	-0.04832
	(0.10700)	(0.10010)	(0.03987)
Altitude	-0.00152	-0.00075	-0.00046
	(0.00016)	(0.00015)	(0.00006)
R^2	0.41101	0.19294	0.33387
N.Obs:	207	207	207

of the territory, or for coastal areas they could have on average lower population density so that it could also be more costly to operate. In facts those variables are significantly negative indicating more difficulty for those regions to reach efficiency. Touristic presences in general are also associated with lower efficiency, presences per resident are significantly and negatively impacting both CRS and VRS scores, although there is no evidence that also affect scale effects scores. Coming to our variable of interest, seasonality, appears to be sizable and significant as well for all measure of efficiency including for scale scores. Its appears therefore clear that seasonality plays a role by itself, worsening significantly the impact of tourism on the efficiency of waste management.

Table 2 reports the same set of regressions with one notable difference within the set of explanatory variables: seasonality is now measured in terms of arrival rather than presences and an additional variable is included to measure the duration of stay at pick season, weighed by the average duration of stay. The literature on the effect of tourism on the environment, and on solid waste management in particular, suggests that fewer tourists that stay longer have a lower negative impact, and this variable should be able to capture this possible effect given the already measured effect of seasonality. The OLS results do not give a definite answer to this question, however it is noticeable that the scale efficient score is positively correlated with the pick length of stay while negatively correlated with the seasonality of arrivals.

As noted before, while OLS regressions are useful because easy to interpret, to run and clearly defined, there are reasons to believe that our data do not satisfy all the assumptions for carrying out correct inference. In particular we should worry about geographically correlated errors arising from not taking into account possible relationships between close municipalities. The following set of estimations are base on the model presented in equation 2 where I consider the same variable used in

Table 3: OLS II

Dependent Variables:	CRS-Efficiency Scores (a)	VRS-Efficiency Scores (b)	SER-Efficiency Scores (c)
Intercept	-0.20389	-0.03080	0.95186
	(0.38286)	(0.35637)	(0.13955)
Pick Arrivals	-0.12612	0.01826	-0.10720
	(0.09043)	(0.08417)	(0.03296)
Pick Duration of Stay	-0.00808	-0.39836	0.19414
	(0.29136)	(0.27120)	(0.10620)
Population	-0.00031	-0.00003	-0.00046
	(0.00182)	(0.00170)	(0.00066)
Presences per Resident	-0.00114	-0.00187	0.00044
	(0.00097)	(0.00090)	(0.00035)
Coastal Area	-0.42806	-0.29168	-0.05951
	(0.10716)	(0.09974)	(0.03906)
Altitude	-0.00153	-0.00071	-0.00050
	(0.00016)	(0.00015)	(0.00006)
R^2	0.41153	0.20178	0.36320
N.Obs:	206	206	206

2 except for the dummy on coastal areas as it appears to be too correlated with the weighing matrix making it impossible for the maximum likelihood algorithm to converge.

Tables 4 and 5 estimates the effect of the exogenous variables on Constant Returns to Scale efficiency scores, tables 6 and 7 the effect on Variable Returns to Scale efficiency score and finally Tables 8 and 9 on Scale Efficiency Ratios. Tables 4, 6 and 8 report the parameter estimation while Tables 5, 7 and 9 the calculated direct, indirect and total effects.

The results from the SAR models shed some more light on the relationship between efficiency and seasonality of tourism. First of all, we can notice that the first two models although they do

Table 4: SAR I - Estimation

Dependent Variable: CRS-Efficiency Scores			
Model			
Parameter	Coefficient	Std. Error	t-stat
Intercept	0.93405	0.37129	2.51567
Pick Arrivals	-0.23461	0.08372	-2.80221
Pick Duration of Stay	-0.23764	0.28273	-0.84051
Population	-0.00282	0.00171	-1.64817
Presences per Resident	-0.00266	0.00091	-2.93005
Altitude	-0.00122	0.00015	-8.05387
ρ	0.79399	0.13125	6.04936
R^2	0.40328		
N.Obs:	212		

Table 5: SAR I - Average Marginal Effects

Dependent Variable: CRS-Efficiency Scores

Parameter	Coefficient	Std. Error	t-stat
Marginal Average Effects Model 1			
Direct Effects			
Pick Arrivals	-0.24079	0.09313	-2.58547
Pick Duration of Stay	-0.25519	0.30167	-0.84591
Population	-0.00296	0.00191	-1.54457
Presences per Resident	-0.00281	0.00098	-2.85984
Altitude	-0.00127	0.00019	-6.56684
Indirect Effects			
Pick Arrivals	-2.29046	4.16733	-0.54962
Pick Duration of Stay	-2.23938	6.14786	-0.36425
Population	-0.02820	0.05842	-0.48270
Presences per Resident	-0.02714	0.04639	-0.58506
Altitude	-0.01223	0.01972	-0.62021
Total Effects			
Pick Arrivals	-2.53124	4.21080	-0.60113
Pick Duration of Stay	-2.49457	6.30798	-0.39546
Population	-0.03116	0.05938	-0.52468
Presences per Resident	-0.02995	0.04686	-0.63920
Altitude	-0.01351	0.01985	-0.68047

Table 6: SAR II - Estimation

Dependent Variable: VRS-Efficiency Scores			
Model			
Parameter	Coefficient	Std. Error	t-stat
Intercept	0.64981	0.35877	1.81123
Pick Arrivals	-0.05195	0.07829	-0.66361
Pick Duration of Stay	-0.56574	0.26352	-2.14685
Population	-0.00172	0.00159	-1.08140
Presences per Resident	-0.00289	0.00084	-3.42759
Altitude	-0.00051	0.00014	-3.56500
ρ	0.55900	0.25674	2.17732
R^2	0.20418		
N.Obs:	212		

Table 7: SAR II - Average Marginal Effects

Dependent Variable: VRS-Efficiency Scores

Parameter	Coefficient	Std. Error	t-stat
Marginal Average Effects Model 1			
Direct Effects			
Pick Arrivals	-0.05383	0.08000	-0.67290
Pick Duration of Stay	-0.58981	0.27899	-2.11410
Population	-0.00183	0.00158	-1.15728
Presences per Resident	-0.00299	0.00094	-3.16789
Altitude	-0.00052	0.00015	-3.47591
Indirect Effects			
Pick Arrivals	-0.18486	1.08553	-0.17030
Pick Duration of Stay	-2.85222	8.21396	-0.34724
Population	-0.00805	0.02838	-0.28351
Presences per Resident	-0.01560	0.04202	-0.37131
Altitude	-0.00256	0.00685	-0.37435
Total Effects			
Pick Arrivals	-0.23869	1.11855	-0.21340
Pick Duration of Stay	-3.44202	8.31751	-0.41383
Population	-0.00988	0.02898	-0.34076
Presences per Resident	-0.01859	0.04243	-0.43811
Altitude	-0.00309	0.00691	-0.44709

show a significant and positive autocovariance signalled by the parameter ρ, they do not indicate significant indirect effect of the exogenous variables on the efficiency scores, it appears therefore that there are not significant spillovers in waste management. Another result that appears clear from the SAR 2 model that was not clear with the OLS is that variable scale efficiency scores are significantly and negatively correlated with the length of stay and not with the pick arrivals, this is opposite for the constant return to scale scores. In other words, when we allow the scale of production to vary presences seem to be the driving force of negative efficiency, while if we keep the scale constant arrival are more important in explaining loss of efficiency. This could suggest that the length of stay helps especially in sizing rightly the scale of operation, an effect that may be driven by factors related to the attachment of tourist to a destination and possibly the easiness to predict their presence and therefore better adjust for scale of operation. Model 3 clarify this point, pick arrival is clearly negative and strongly significant, while the length of stay positive and also significant. Therefore, efficiency of scale is impacted negatively by the seasonality in arrival while positively by the length of stay. Model 3 also shows a negative spatial autocovariance and a significant positive indirect effect of pick arrivals, although not very sizable compared to the direct one.

Overall, putting together the information that the set of three models bring to us it seems clear

Table 8: SAR III - Estimation

Dependent Variable: SER-Efficiency Scores			
Model			
Parameter	Coefficient	Std. Error	t-stat
Intercept	1.13534	0.13791	8.23247
Pick Arrivals	-0.10830	0.03048	-3.55256
Pick Duration of Stay	0.20674	0.10334	2.00062
Population	-0.00078	0.00061	-1.27397
Presences per Resident	0.00035	0.00033	1.07053
Altitude	-0.00040	0.00006	-6.48718
ρ	-0.26795	0.11663	-2.29733
R^2	0.36483		
N.Obs:	212		

Table 9: SAR III - Average Marginal Effects

Dependent Variable: SER-Efficiency Scores

Parameter	Coefficient	Std. Error	t-stat
Marginal Average Effects Model 1			
Direct Effects			
Pick Arrivals	-0.10987	0.02976	-3.69220
Pick Duration of Stay	0.20513	0.10234	2.00443
Population	-0.00076	0.00061	-1.26219
Presences per Resident	0.00036	0.00034	1.07023
Altitude	-0.00040	0.00007	-6.15276
Indirect Effects			
Pick Arrivals	0.02165	0.01002	2.16072
Pick Duration of Stay	-0.04282	0.02907	-1.47333
Population	0.00015	0.00015	1.06032
Presences per Resident	-0.00008	0.00008	-0.94137
Altitude	0.00008	0.00003	2.59909
Total Effects			
Pick Arrivals	-0.08822	0.02721	-3.24186
Pick Duration of Stay	0.16231	0.08066	2.01217
Population	-0.00061	0.00049	-1.25803
Presences per Resident	0.00029	0.00027	1.05270
Altitude	-0.00032	0.00007	-4.35050

that seasonality has a negative effect on the efficiency of solid waste management, that this effect is primarily due to the difficulty to operate at optimal scale and that it is especially the seasonality of arrivals that negatively impacts efficiency while the average stay at pick season has an opposed positive effect.

4 conclusions

Tourism is traditionally associated with great opportunities of growth with relatively small investments in physical and human capital, but also with high levels of negative externalizes. The aim of this paper is to bring evidence of the environmental cost of tourism in terms of solid waste management efficiency in Tuscan municipalities, with particular focus on the seasonality of tourism. This paper fills the gap in the literature that has not investigated so far how tourism typically manifests itself, that is with highly seasonal increases of presences. The results collected in the paper confirm previous studies that report an important impact of tourism on the efficiency of solid waste management operations, also relating it to the difficulty to reach optimal scales. In addition, the results clearly indicate an additional affect of seasonality of tourism, that is, when touristic presences are unevenly distributed over the year the effect of tourism is stronger, as seasonality has an additional effect. They also show that this additional effect comes through scale effects, that is, as intuitively we could predict, seasonality makes it more difficult to manage solid waste at optimal scales. Finally, conditional on the size of touristic seasonal flow of presences, it is to prefer a lower number of tourists that stay longer to a larger number of short stays. The implications of these results are clear, more effort has to be made in managing flexibly solid waste collection in those localities affected mostly by seasonal tourism, as well as efforts are also to be made in trying to spread more tourism over the year. A more punctual and immediately applicable policy to counter the seasonal effect could also be a flexible taxation of touristic presences, a tax that could be thought as a function of predicted congestion of presences to counter the negative externalities associated with it.

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